Algorithm selection and configuration for Noisy Intermediate Scale Quantum methods for industrial applications

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